2-D Processing of Speech
with Application to Pitch and Formant Estimation*

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Speech and Audio Signal Processing

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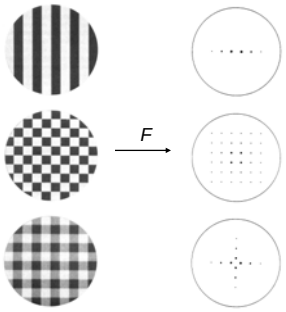
Motivation
From Image Processing

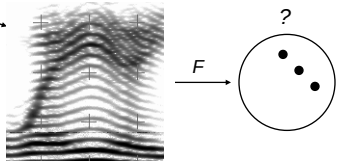
- **Certain 2-D geometric patterns transform to dots in a 2-D spatial frequency plane***
- **Time-frequency distributions contain "geometric patterns" due to harmonic content**
  - **Possible use**
    - **Pitch estimation**
    - **Noise reduction**
    - **Multi-speaker separation**

**From R.L. DeValois and K.K. DeValois, *Spatial Vision*, Oxford University Press, 1988.*

2-D Grating Patterns



Narrowband Spectrogram



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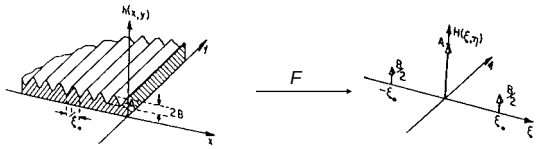
OUTLINE

- **2-D Spectrogram Model and Mapping**
- **Application to Pitch Estimation**
- **Application to Formant Estimation**
- **Extension to Alternate Time-Frequency Distributions**
- **Conclusions and Directions**

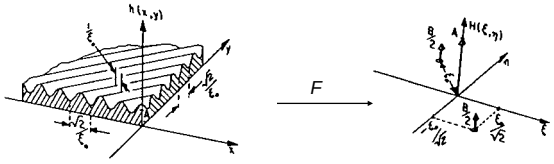
2-D Spectrogram Model
Inspiration from Image Processing

- **2-D sine on a pedestal*: Zero degree rotation**



Distance of 2-D impulses from origin varies inversely with sine frequency

- **2-D sine on a pedestal*: 45 degree rotation**



Angle of 2-D impulses w/r axes proportional to extent of sine rotation

From J.D. Gaskill, *Linear Systems, Fourier Transforms, and Optics*, John Wiley and Sons, New York, NY, 1978.

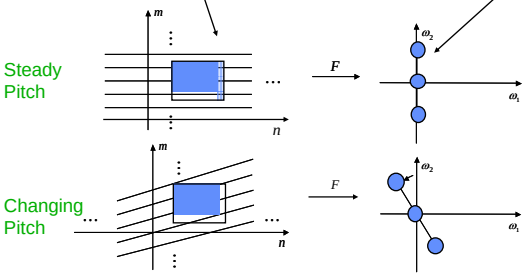
2-D Spectrogram Model

Short-Space 2-D Sine

- **Harmonic line structure of the narrowband spectrogram is modeled over a <u>small region</u> by a 2-D sine function sitting on a flat pedestal of unity**
- **2-D window is applied to extract a short-time segment and 2-D Fourier transform is then computed**

$$x[n,m] = w[n,m](1+\cos(\omega_g m))$$

$$X(\omega_1,\omega_2) = 2W(\omega_1,\omega_2) + W(\omega_1,\omega_2-\omega_g) + W(\omega_1,\omega_2+\omega_g)$$



2-D Impulses are smeared by 2-D windowing

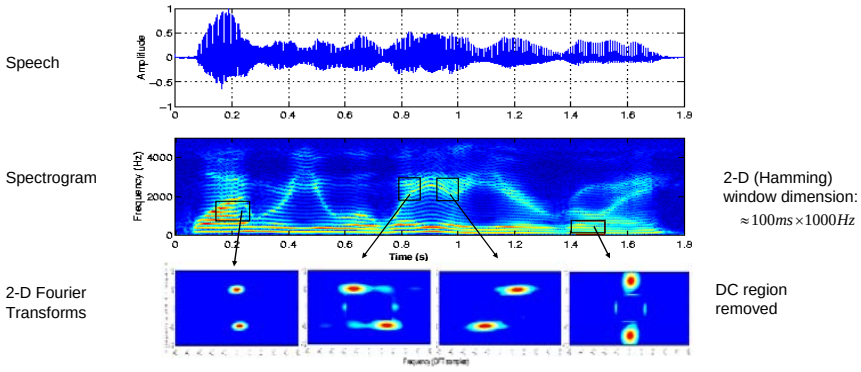
Distance from origin of smeared impulses varies inversely with pitch

Angle of impulses from vertical axis varies with pitch dynamics

2-D Processing

Example

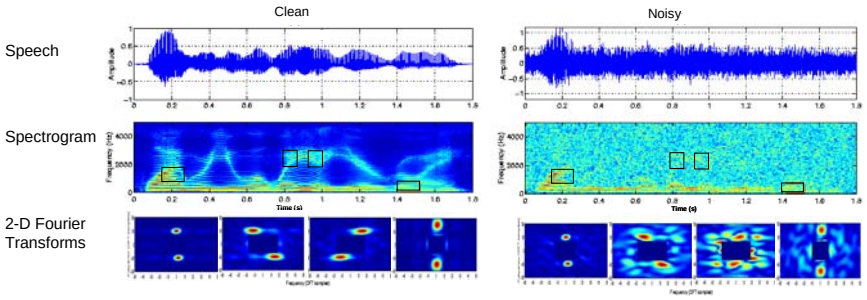
- **2-D analysis of narrowband spectrogram of all-voiced female speech**



Henceforth, refer to 2-D mapping as the "<u>G</u>rating <u>C</u>ompresssion <u>T</u>ransform" (GCT) to highlight mapping "gratings" to concentrated "dots"

2-D Processing
Example with Noise

- **2-D analysis of all-voiced female speech in noise**
  - **GCT without and with additive white Gaussian noise at average SNR of ~3 dB**



- **Energy concentration of GCT is typically preserved at roughly the same location as for the clean case**
  - **However, when noise dominates so that little harmonic structure remains within the 2-D window, energy concentration deteriorates, as in the vicinity of 0.95 s and 2000 Hz**

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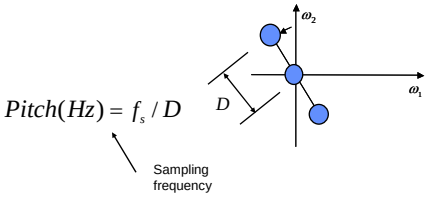
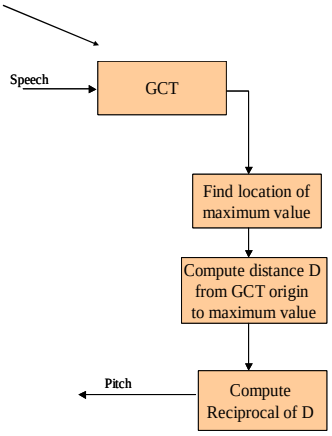
Pitch Estimation
GCT-Based Approach

- GCT of speech examples motivate a simple pitch estimator
  - Pitch estimate is reciprocal to the distance from the origin to the maximum value in the GCT

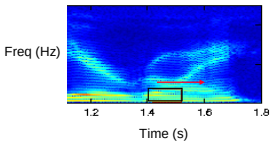




- Pitch rate of change is proportional to angle of GCT peak from vertical axis

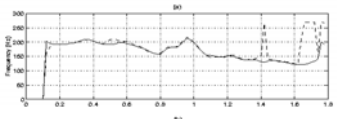
GCT-Based Pitch Estimation
Example

- GCT-based estimator over time
  - 2-D analysis window slid along the speech spectrogram at a 10-ms frame interval at low-frequency location

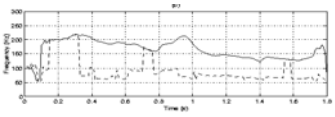


  - Relatively robust in noise, out-performing a sinewave-based pitch estimator

GCT-Based Estimator



Sinewave-Based Estimator



Solid: Clean Speech
Dashed: 3 dB SNR

GCT-Based Pitch Estimation
Performance

- **GCT-based estimator**
  - **2-D analysis window slid along the speech spectrogram at a 10-ms frame interval at a low-frequency location given by the 2-D window in previous slide**
  - **Average magnitude difference measured between pitch-contour estimates with and without white Gaussian noise for both the GCT- and sinewave-based estimators**

Performance Measurements

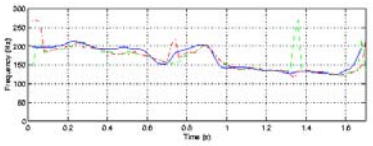
	FEMALES		MALES	
	9dB	3dB	9dB	3dB
GCT	0.5	6.7	0.9	6.7
SINE	5.8	40.5	2.6	12.8

Average magnitude error (in dB) in GCT- and sine-wave-based pitch contour estimates for clean and noisy all-voiced passages. The two passages "Why were you away a year Roy?" and "Nanny may know my meaning." from two male and two female speakers were used under noise conditions 9 dB and 3 dB average signal-to-noise ratio.

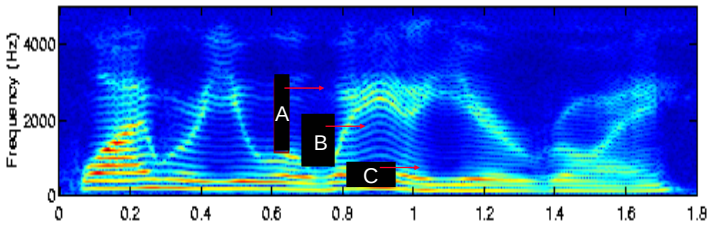
Pitch Estimation
Multi-resolution properties

- **Pitch in the 2-D plane**
  - **Pitch can be obtained anywhere in the 2-D plane**
  - **"Wavelet-like tiling" of 2-D window found to give the most consistent estimate**
    - **Reflects increase pitch FM with increasing frequency**

Three pitch contours

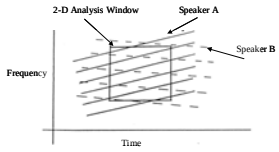


Window A: Dashed Green
Window B: Dashed-Dot Red
Window C: Solid Blue

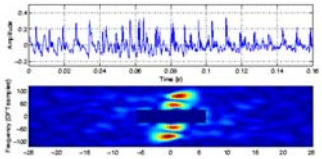


Two-Speaker Pitch Estimation

- Sum of two speakers has spectrogram with two harmonic sets

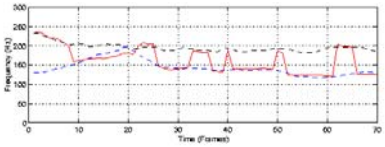


- GCT gives two pairs of dots, one pair for each speaker
  - All-voiced example (male + female)



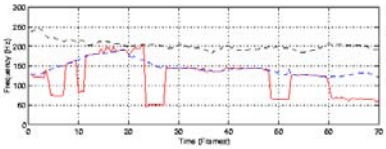
- Blind use of one-speaker pitch estimator on two-speaker signal

GCT-Based Estimator



Maximun of GCT latches on to speaker with (locally) largest energy

Sine-Wave-Based Estimator



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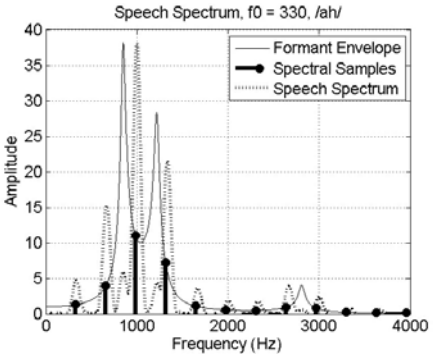
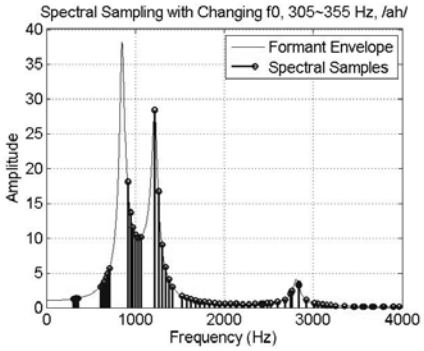
Formant Estimation

The High-Pitched Problem

Synthesized vowel /ah/ with 330-Hz pitch. Speech spectrum generated from short-time Fourier analysis with a 20-ms Hamming window.

Collection of harmonic samples from pitch sweep ranging from 305~355 Hz. Contrast to *f0* = 330 Hz shown in Figure 1.

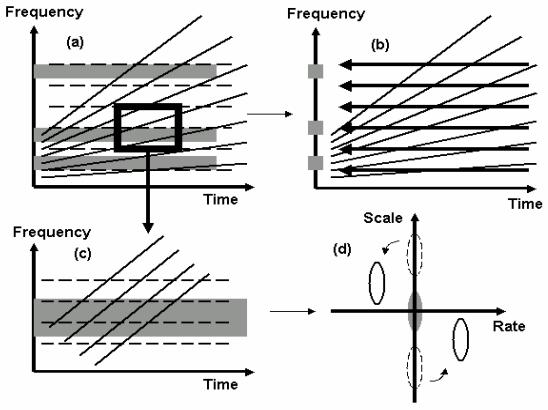




2-D Framework

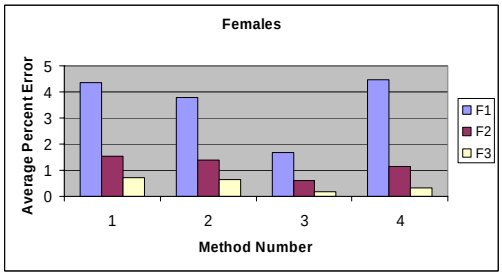
Exploiting Changing Pitch in Formant Estimation

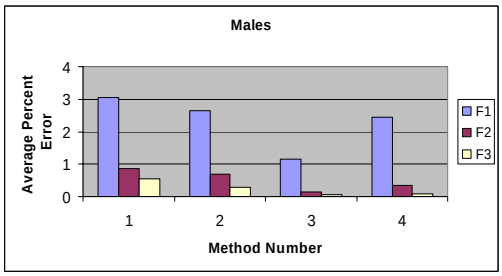
a) Schematic of changing and fixed *f0* across a steady vowel in a STFT; (b) Averaging of harmonic samples to a single 1-D frequency axis; (c) Localized spectrotemporal region from (a); (d) Mapping of source-filter speech components in the GCT from (c).



Spectral Estimation: Results

Average Percent Formant Error

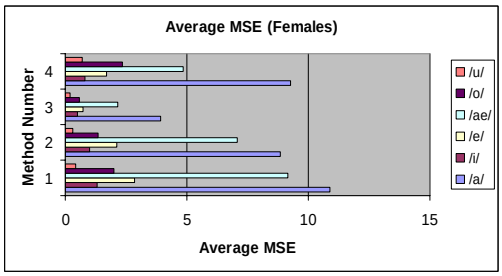


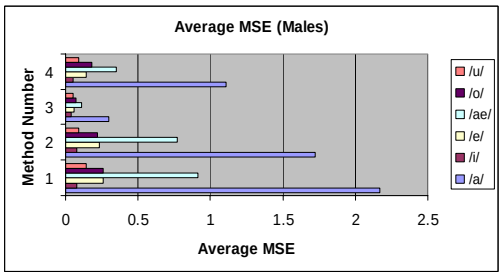


- **Methods**
  1. **Single STFT slice**
  2. **Cepstral liftering**
  3. **Proposed method**
  4. **Spectral slice averaging**
- **Relative gains (method 1) for [F1, F2, F3] via proposed:**
  - **Females: [61%, 61%, 73%]**
  - **Males: [62%, 82%, 87%]**
- **Gains for F3 greatest (wider harmonic sampling)**
- **Individual formant scores *across* vowels also consistent**

Spectral Estimation: Results

Average MSE



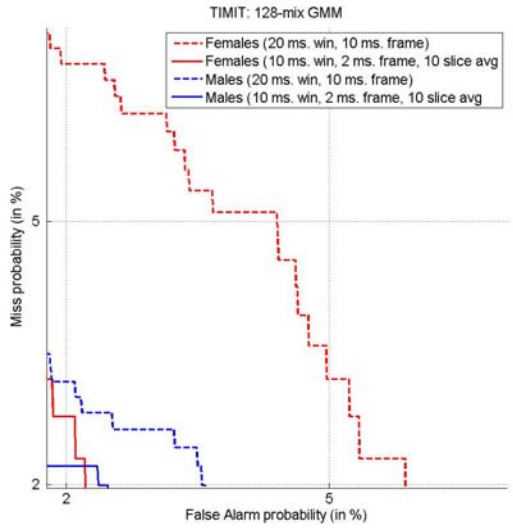


- **Methods**
  1. **Single STFT slice**
  2. **Cepstral liftering**
  3. **Proposed method**
  4. **Spectral slice averaging**
- **Results are consistent with formant frequency estimation**
  - **Method 3 outperforms others for all vowels**
- **Data not shown:**
  - **Consistent results with children's formants**

Speaker Recognition: Methods

- Data set - male and female subsets of TIMIT corpus
- Baseline system
  - Mel-cepstrum feature extraction with 20 ms. window and 10 ms frame interval + delta features
  - Adaptive Gaussian Mixture Modeling
    - 128 mixture components
    - Universal background model
- System modifications in *feature extraction*
  - Short-time analysis using 10 ms frame window and 2 ms frame interval
  - Compute *average* of spectral slices spanning ~30 ms
  - Derived spectra are used for computing standard mel-cepstrum + deltas

Speaker Recognition: Results



- Equal error rate (EER)

	Baseline (EER)	Proposed (EER)
Males	1.86%< 2.45% < 3.39%	1.53% < 2.15% < 2.80%
Females	3.12%< 4.41% < 5.64%	1.55% < 2.15% < 3.30%

- Absolute EER reduction in females 2.26% (not yet significant)

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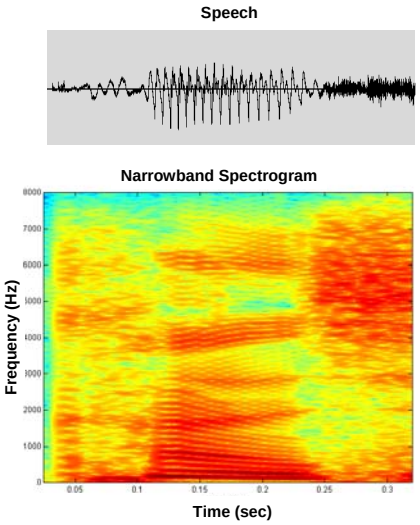
Limitation of the Spectrogram
Observations

- Two curious effects are seen:
  - Frequency tracks moving in the wrong direct, e.g., up rather than down and
  - Crossing tracks, i.e., tracks moving up and down simultaneously.
- The problem is that the basis functions of the Fourier transform, stationary sinusoids, cannot resolve the speech harmonics which have rapid frequency modulation and are closely spaced in frequency.
  - This lack of resolution leads to the complex line phenomena seen in Figure 2.

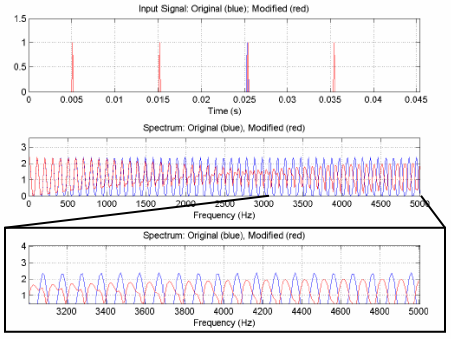


Spectral Sensitivity*

Example

- Harmonic speech spectra can be quite sensitive to aberrations in periodicity of the glottal source
- Even small perturbations can lead to short-time spectral changes that mislead the viewer in terms of signal composition

Example: One-sample shift (0.1 ms)



We see that the shift in time domain seems to move the harmonics in the higher frequencies

*We have developed formal spectral for these sorts of effects: To be published in January 2008 IEEE TSLP, "Spectral representations of nonmodal phonation," Malyska and Quatieri.

An Alternate Transform

The Fan-Chirp Transform

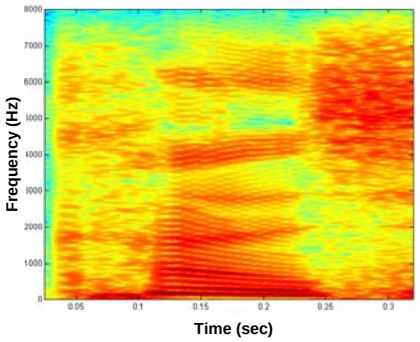
- The Fan-Chirp Transform (FChT)
  - "Adaptive Chirp-Based Time–Frequency Analysis of Speech Signals"
    Marian Kepesia and Luis Weruaga, *Speech Communication*, vol. 48, no. 5, pp. 474-492, May 2006.
  - "The Fan-Chirp Transform for Non-Stationary Harmonic Signals"
    Luis Weruaga and Marian Kepesia, (submitted to Elsevier)
- FChT is a generalization of the Fourier transform
  - Fourier transform basis functions are stationary sine waves
  - FChT basis functions are sine waves with linear frequency modulation
    - the set of basis functions has a fan geometry
    - 1st order match to harmonic frequency modulation in speech

Spectrogram Comparison

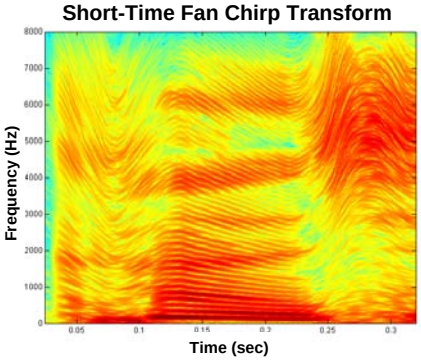
STFT versus Short-Time Fan-Chirp

- **Observations**
  - **FChT resolves high frequency harmonics even when frequency modulation is large**
  - **Frequency tracks appear as predicted for FChT**

Short-Time Fourier Transform



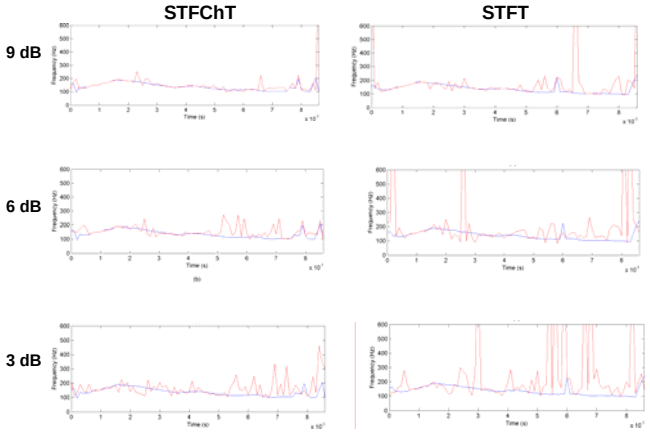
Short-Time Fan Chirp Transform



Fan-Chirp for Grating Compression Transform

Pitch Estimation

- **Based on preliminary results, for pitch estimation in noise, the short-time Fan-chirp tranform appears to outperform the STFT**



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Conclusions and Directions

- The grating compression transform (GCT) maps harmonically-related signal components to a concentrated entity in a spatial 2-D frequency plane
- The GCT forms the basis of a pitch estimator that uses the radial distance to the largest peak of the GCT
  - The resulting pitch estimator appears robust under noise conditions and amenable to extension to two-speaker pitch estimation
- The GCT forms the basis of a formant estimator that exploits separability of speech source and vocal tract information via changing pitch
- Although the spectrogram provides a useful starting point for the GCT, alternate transforms can provide improved performance
  - Fan-chirp transform is one possibility
- Possible GCT directions
  - Alternate time-frequency distributions
  - Pitch estimation
    - Extended evaluation to a larger corpus and use of voiced/unvoiced speech
    - Two-speaker pitch estimation
  - Formant estimaiton in noise
  - GCT as model of auditory cortical processing (Sthamma, Ezzat, and Poggio)